Review-Based Domain Disentanglement without Duplicate Users or Contexts for Cross-Domain Recommendation

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Source : CIKM'22

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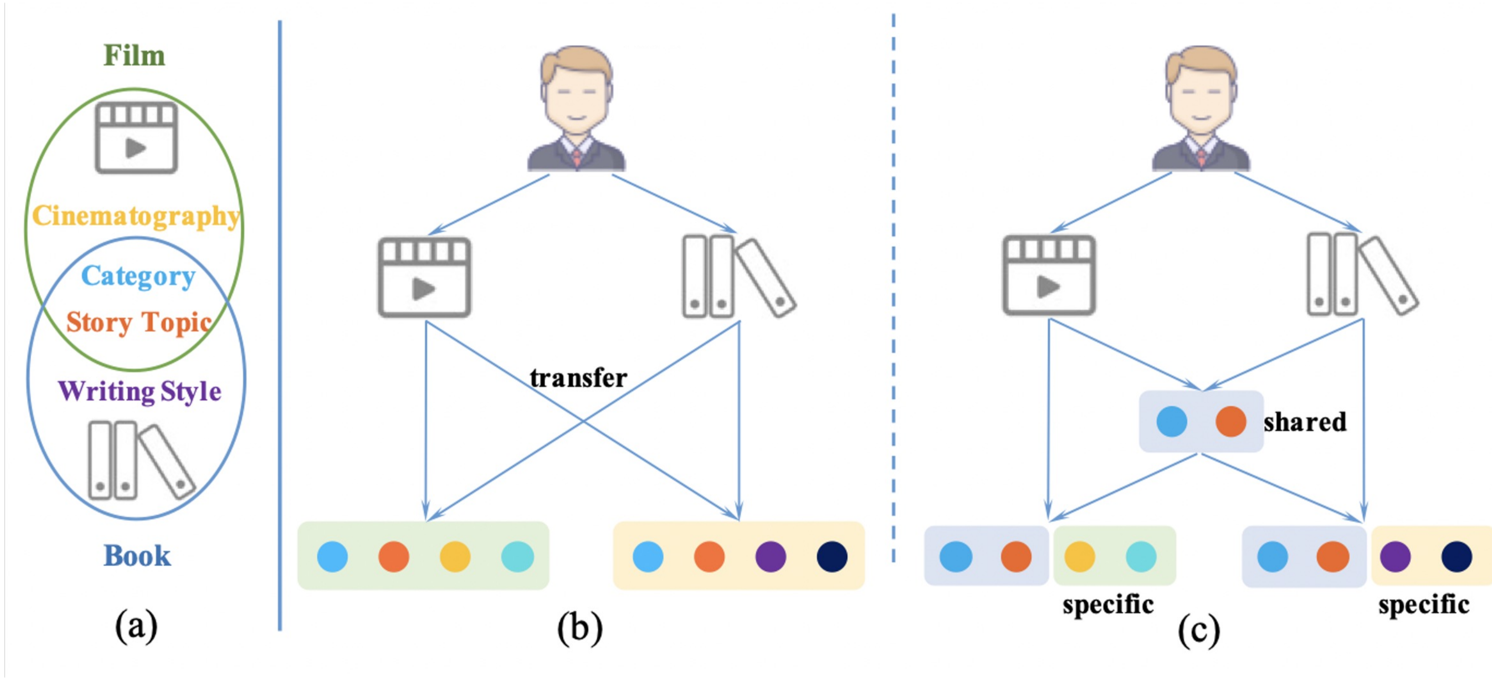
Outline

- **Introduction**
- Method
- Experiment
- Conclusion

Cross-Domain Recommendation

- Using information from source domain to alleviate the cold-start problem in the target domain.



Input:

- user u
- Aggregated reviews for users : Ru
- item i
- Aggregated reviews for items : Ri
- individual review ru,i

Output:

- rating yu,i

Outline

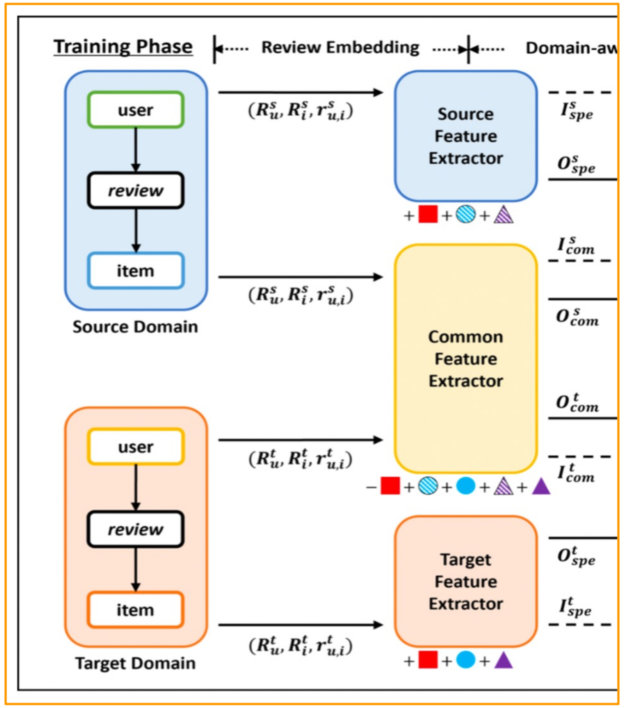
- Introduction
- **Method**
    - Review Embedding
    - Domain-aware Feature Extraction
    - Encoding Network and Regressor
- Experiment
- Conclusion

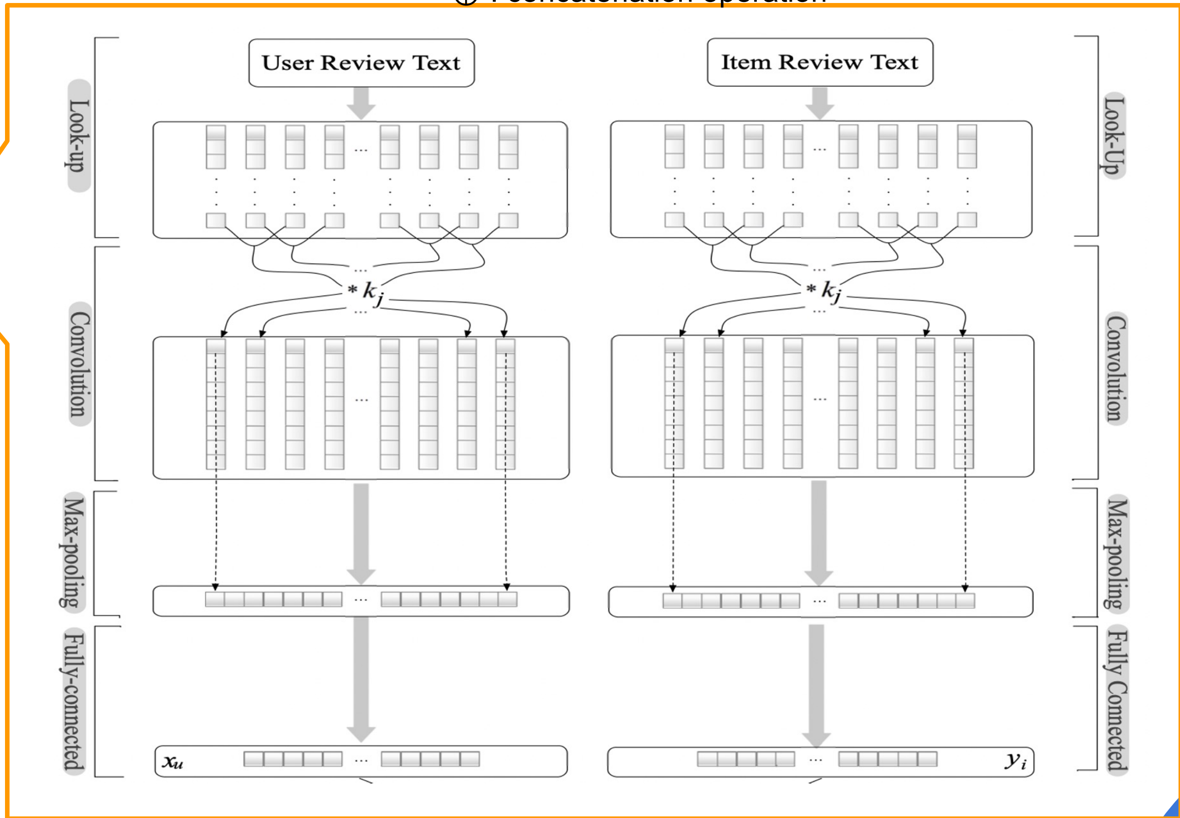
Review Embedding Layer

$$V = \phi(w_1) \oplus \phi(w_2) \oplus \dots \oplus \phi(w_n)$$

ϕ : embedding operation

$\oplus$: concatenation operation





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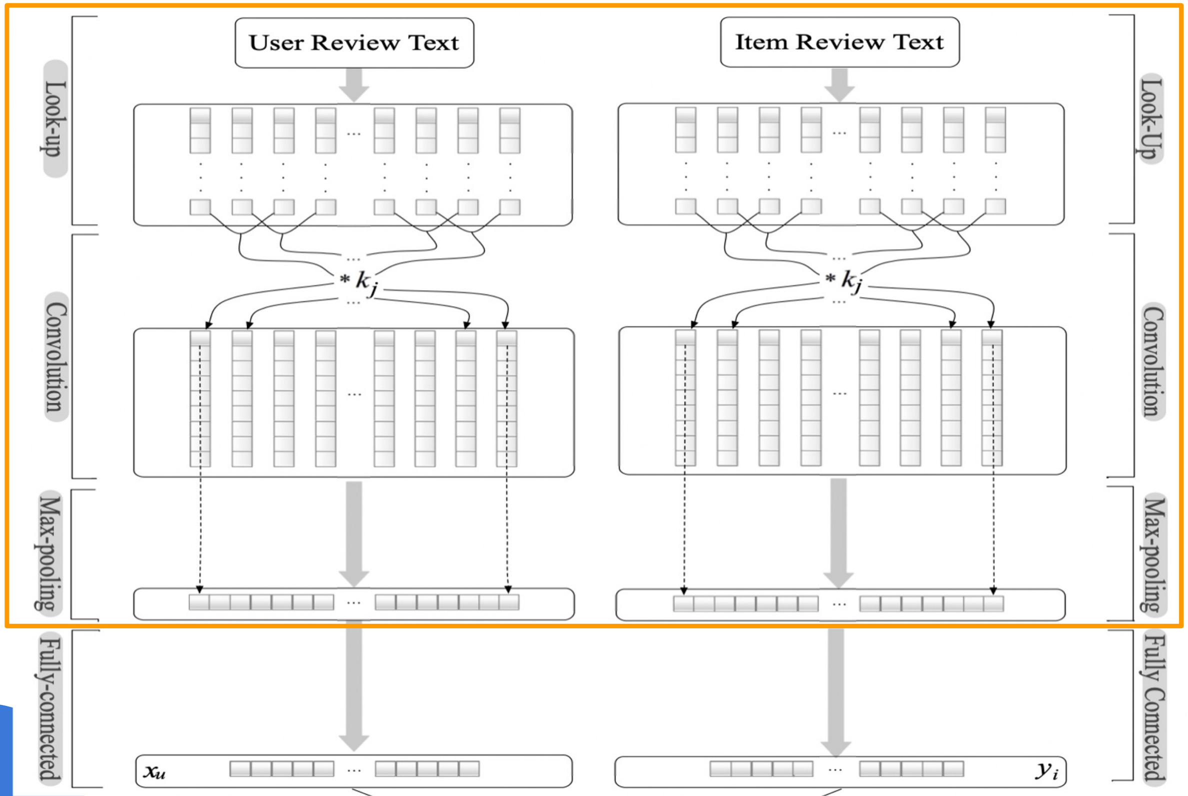
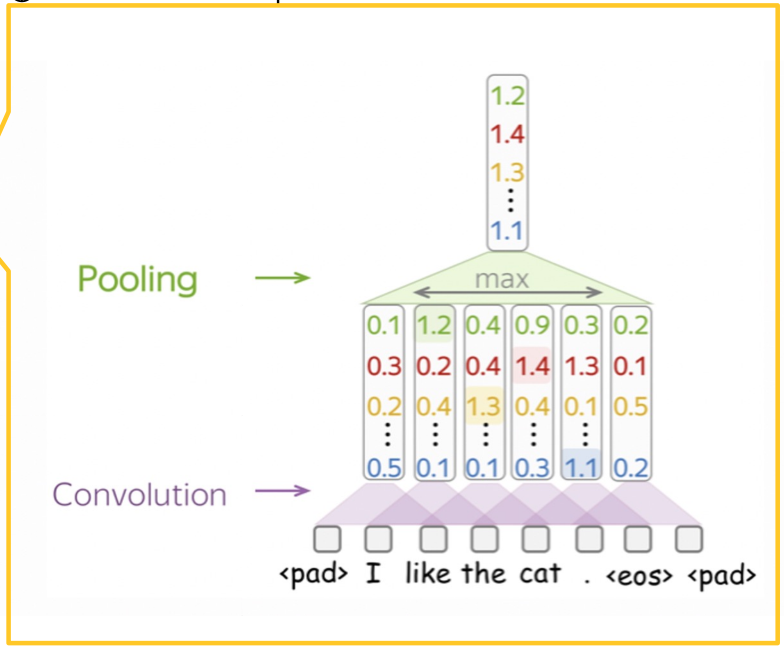
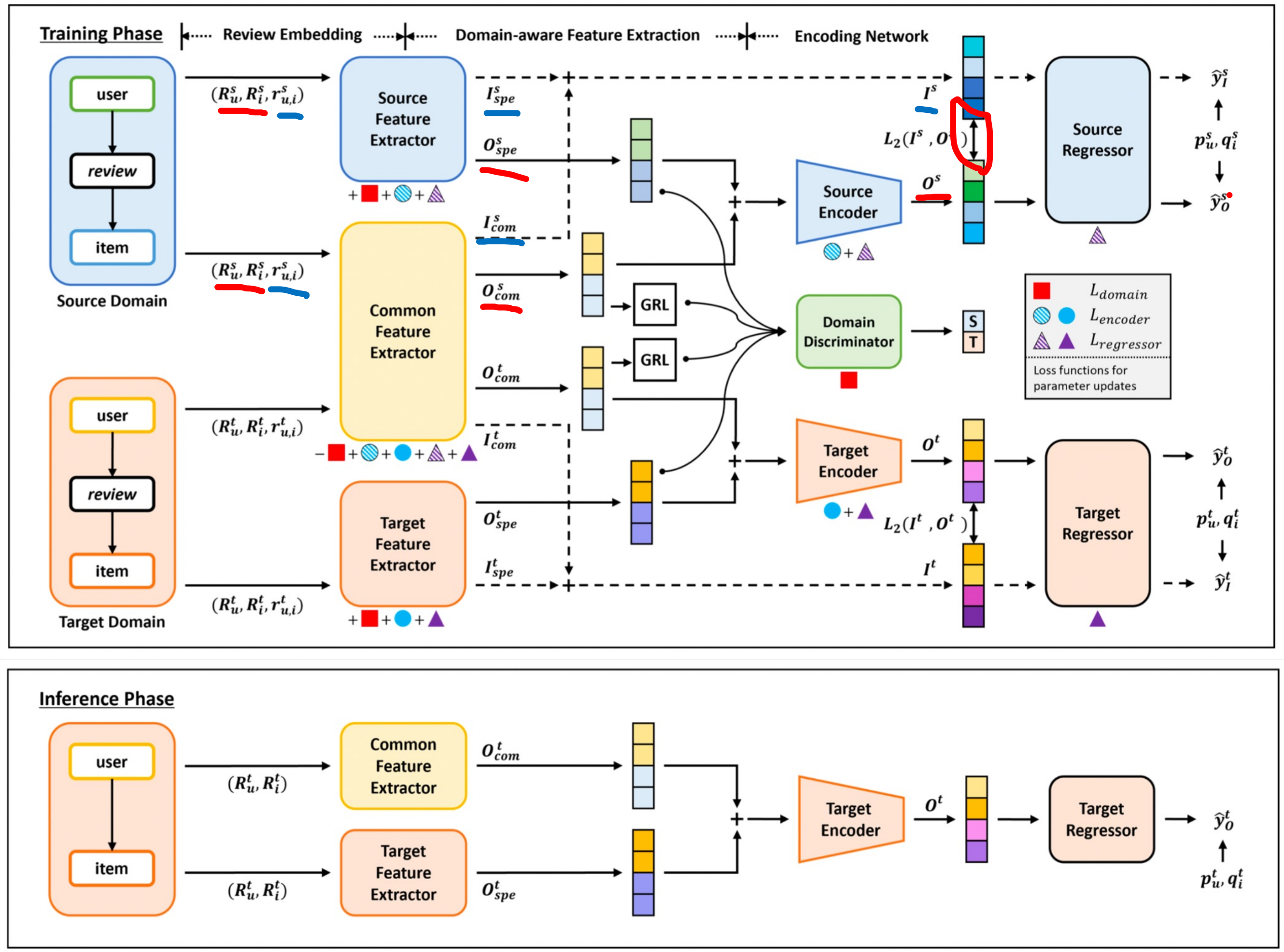




Encoding Network

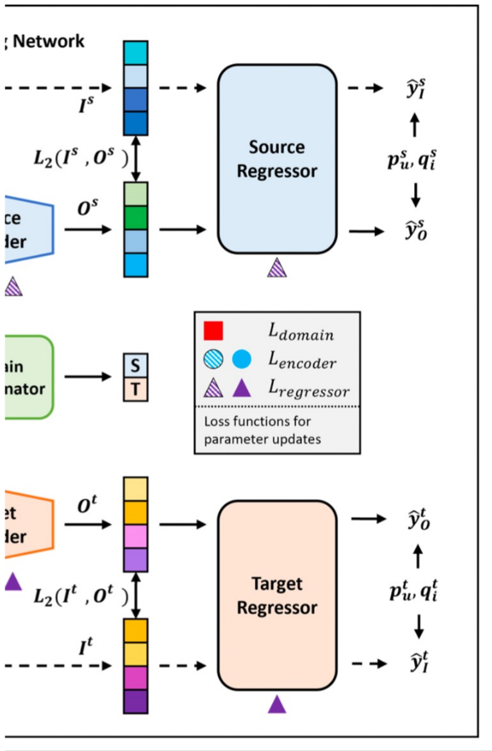


$$O = F_{enc}(O_{spe} + O_{com})$$

$$I = I_{spe} + I_{com}.$$

$$\mathcal{L}_{enc}^{d} = \frac{1}{N_d}\sum_{d=1}^{N_d} ||O^d - I^d||_2^2.$$

Regressor



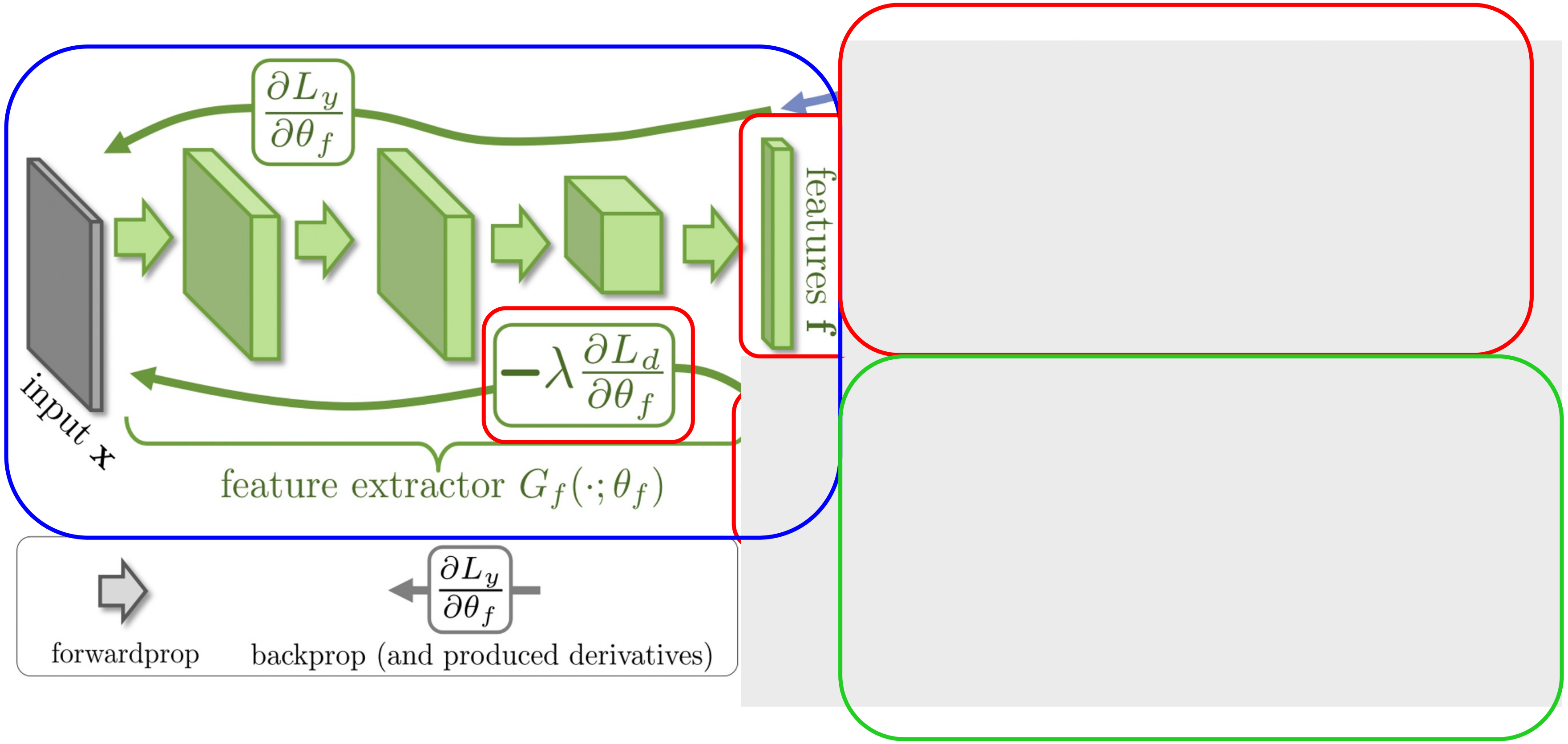
$$\widehat{y}_I = F_{reg}(I) + p_u \cdot q_i^T, \ \widehat{y}_O = F_{reg}(O) + p_u \cdot q_i^T.$$

$$\mathcal{L}_{reg}^d = \frac{1}{2N_d} \sum_{d=1}^{N_d} \left((\widehat{y}_I^d - y^d)^2 + (\widehat{y}_O^d - y^d)^2 \right).$$

pu, qi: embedding of user and item

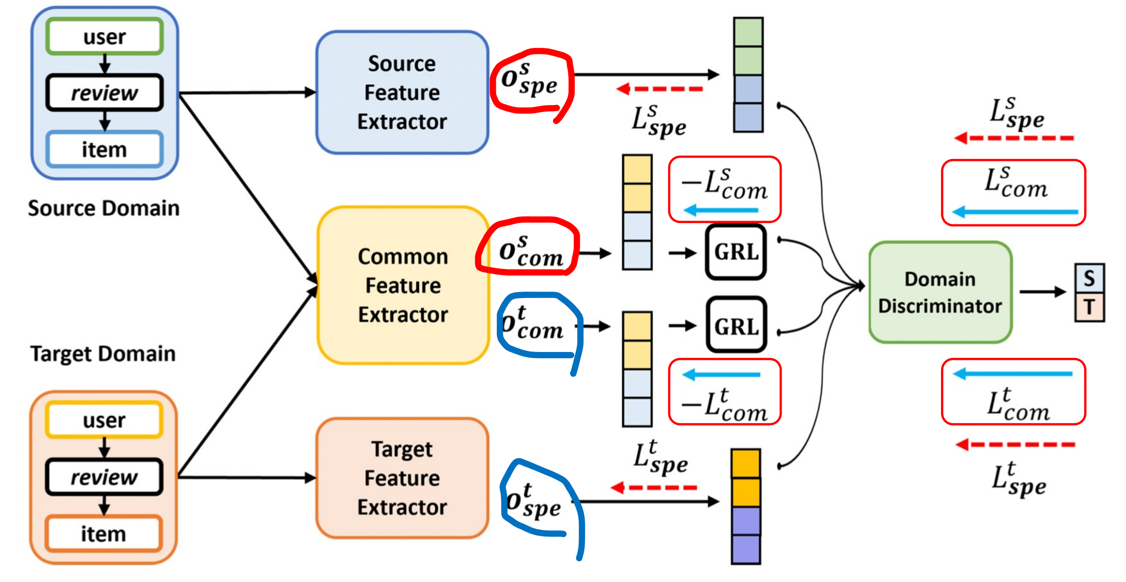
Gradient Reversal Layer

Source domain



Target domain

Domain-aware Feature Extraction



$$\widehat{d}^s_{spe} = F_{disc}(O^s_{spe}),\ \widehat{d}^t_{spe} = F_{disc}(O^t_{spe}),$$

$$\mathcal{L}^s_{spe} = -\frac{1}{N_s}\sum_{s=1}^{N_s} log\boxed{(1-\widehat{d}^s_{spe})},\ \mathcal{L}^t_{spe} = -\frac{1}{N_t}\sum_{t=1}^{N_t} log(\widehat{d}^t_{spe}).$$

$$\widehat{d}^s_{com} = F_{disc}(O^s_{com}),\ \widehat{d}^t_{com} = F_{disc}(O^t_{com}).$$

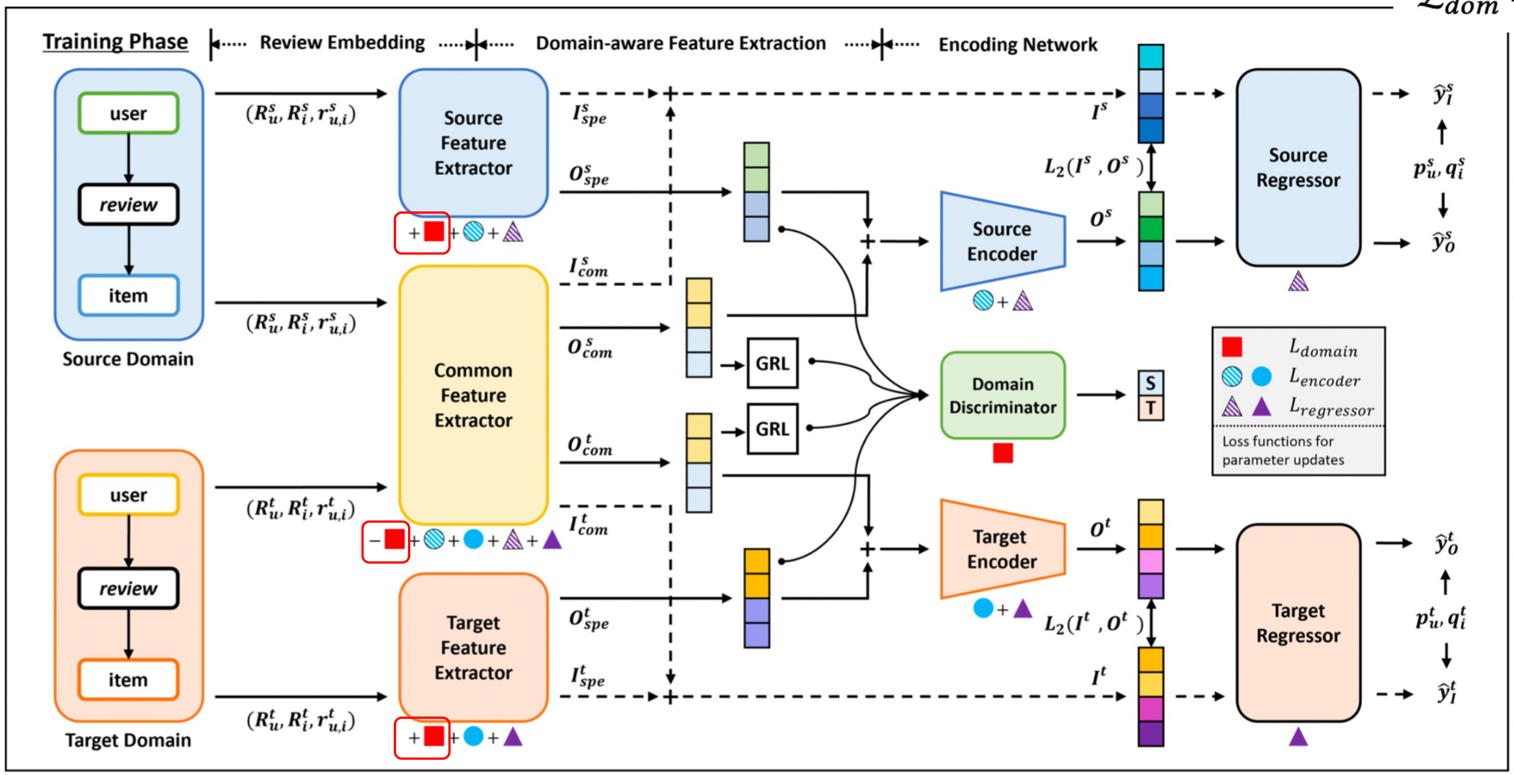
$$\mathcal{L}^s_{com} = -\frac{1}{N_s}\sum_{s=1}^{N_s} log\boxed{(1-\widehat{d}^s_{com})},\ \mathcal{L}^t_{com} = -\frac{1}{N_t}\sum_{t=1}^{N_t} log(\widehat{d}^t_{com}).$$

$$\mathcal{L}_{dom} = a(\mathcal{L}^s_{com} + \mathcal{L}^s_{spe}) + (1-a)(\mathcal{L}^t_{com} + \mathcal{L}^t_{spe}).$$

$$a = \frac{N_s}{N_s+N_t}$$

Loss function

$$\min_{\theta} \mathcal{L} = \alpha \mathcal{L}_{dom} + \beta(\mathcal{L}^s_{enc} + \mathcal{L}^t_{enc}) + \gamma(\mathcal{L}^s_{reg} + \mathcal{L}^t_{reg}) + \delta||\theta||.$$



$$\mathcal{L}_{dom} = a(\mathcal{L}^s_{com} + \mathcal{L}^s_{spe}) + (1-a)(\mathcal{L}^t_{com} + \mathcal{L}^t_{spe}).$$

$$\mathcal{L}^d_{enc} = \frac{1}{N_d}\sum_{d=1}^{N_d} ||O^d - I^d||^2_2.$$

$$\mathcal{L}^d_{reg} = \frac{1}{2N_d}\sum_{d=1}^{N_d}\left((\hat{y}^d_I - y^d)^2 + (\hat{y}^d_O - y^d)^2\right).$$

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Experiment

- ## Dataset

All from Amazon except Yelp

	Dataset	# users	# items	# reviews
Source	Baby	19,445	7,050	160,792
	Kindle Store (KS)	68,223	61,934	982,619
	Toys and Games (TG)	19,412	11,924	167,597
	Yelp	1.9 M	0.2 M	8.1 M
Target	Office Products	4,905	2,420	53,258
	Instant Video	5,130	1,685	37,126
	Automotive	2,928	1,835	20,473
	Patio Lawn and Garden	1,686	962	13,272

Experiment

- **Baselines**
  - Single-domain
  - Cross-domain

- **Evaluation**
  - Mean Squared Error(MSE) (↓)
  - Normalized Discounted Cumulative Gain(nDCG@5) (↑)

$$nDCG_p = \frac{DCG_p}{IDCG_p}$$

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{log_2(i+1)} \qquad IDCG_p = \sum_{i=1}^{|REL_p|} \frac{2^{rel_i} - 1}{log_2(i+1)}$$

Experiment

MSE(↓)

	Target domain	Office Product				Instant Video				Automotive				Patio Lawn and Garden			
	Source domain	Baby	KS	TG	Yelp	Baby	KS	TG	Yelp	Baby	KS	TG	Yelp	Baby	KS	TG	Yelp
Single-domain	PMF	1.085				1.129				1.162				1.177			
	NeuMF	0.974				1.014				1.087				1.143			
	DeepCoNN	0.902				0.949				0.979				1.128			
	NARRE	0.863				0.914				0.887				1.108			
	AHN	0.859				0.892				0.863				1.094			
Cross-domain	DANN	0.966	0.939	0.943	1.118	0.986	0.946	0.987	1.147	0.946	0.881	0.945	1.183	1.129	1.189	1.199	1.395
	DAREC	0.989	0.988	0.972	0.994	1.060	1.045	1.043	1.073	1.001	0.997	0.993	1.004	1.123	1.151	1.131	1.150
	DDTCDR	0.954	0.947	0.926	0.965	0.974	0.981	0.967	0.988	0.961	0.959	0.954	0.969	1.109	1.111	1.105	1.133
	RC-DFM	0.834	0.839	0.828	0.841	0.878	0.855	0.868	0.872	0.792	0.800	0.794	0.802	1.094	1.096	1.109	1.112
	CATN	0.875	0.872	0.873	0.876	0.915	0.906	0.892	0.919	0.824	0.831	0.826	0.837	1.141	1.144	1.129	1.149
	MMT	0.815	0.820	0.822	0.856	0.862	0.855	0.878	0.871	0.818	**0.798**	0.800	0.833	1.116	1.099	1.094	1.117
	SER	**0.789**	**0.815**	**0.810**	**0.806**	**0.852**	**0.833**	**0.855**	**0.847**	**0.785**	**0.798**	**0.769**	**0.784**	**1.028**	**1.029**	**1.039**	**1.033**

Experiment

nDCG@5(↑)

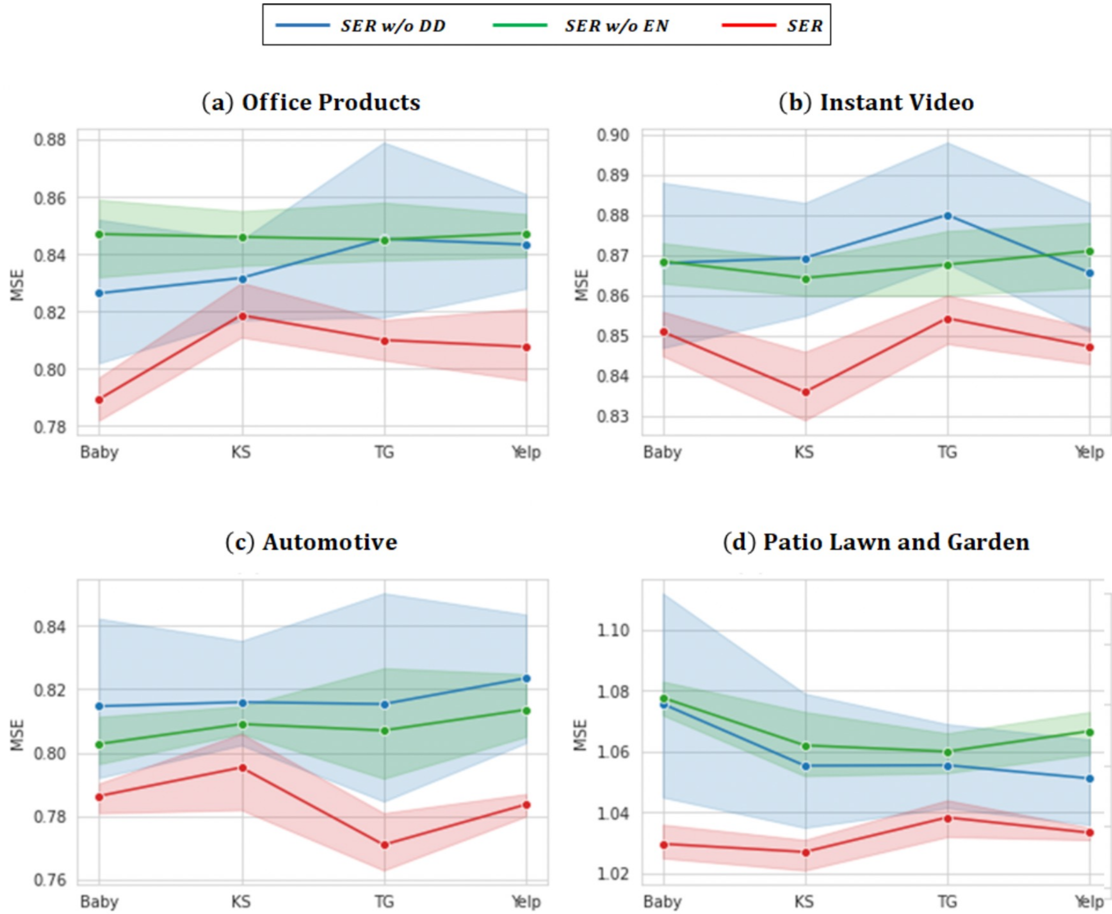
	Target domain	Office Product				Instant Video				Automotive				Patio Lawn and Garden			
	Source domain	Baby	KS	TG	Yelp	Baby	KS	TG	Yelp	Baby	KS	TG	Yelp	Baby	KS	TG	Yelp
Single-domain	PMF	0.737				0.759				0.764				0.770			
	NeuMF	0.756				0.788				0.781				0.776			
	DeepCoNN	0.856				0.840				0.816				0.842			
	NARRE	0.861				0.872				0.851				0.844			
	AHN	0.874				0.879				0.862				0.878			
Cross-domain	DANN	0.843	0.847	0.840	0.829	0.851	0.849	0.846	0.835	0.844	0.858	0.836	0.831	0.830	0.823	0.818	0.812
	DAREC	0.859	0.842	0.835	0.827	0.844	0.848	0.841	0.823	0.865	0.872	0.872	0.860	0.854	0.852	0.861	0.835
	DDTCDR	0.854	0.853	0.860	0.847	0.852	0.858	0.849	0.840	0.877	0.874	0.881	0.865	0.846	0.851	0.849	0.839
	RC-DFM	0.875	0.871	0.880	0.869	0.890	0.884	0.881	0.879	0.884	0.895	0.899	0.902	0.878	0.873	0.871	0.879
	CATN	0.869	0.865	0.871	0.842	0.873	0.857	0.860	0.873	0.866	0.863	0.872	0.875	0.864	0.861	0.858	0.854
	MMT	0.881	0.874	0.870	0.883	0.888	0.885	0.876	0.883	0.886	0.896	0.892	0.877	0.867	0.869	0.871	0.871
	SER	**0.891**	**0.885**	**0.888**	**0.889**	**0.896**	**0.892**	**0.889**	**0.895**	**0.892**	**0.901**	**0.908**	**0.913**	**0.889**	**0.882**	**0.885**	**0.883**

Experiment

Evaluation: MSE(↓)

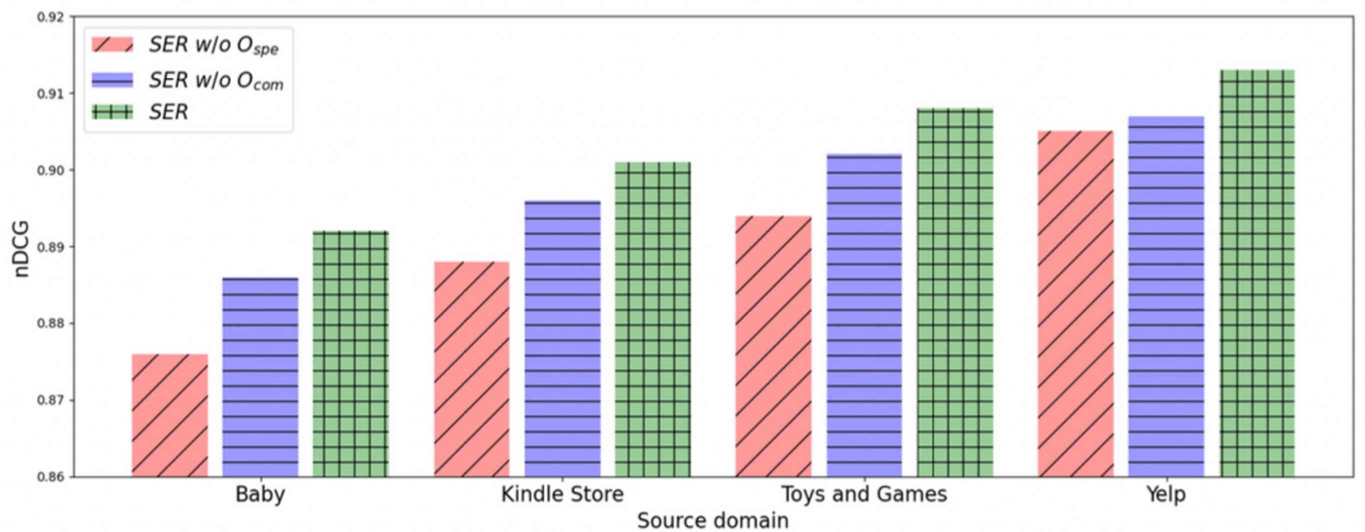
SER w/o DD: excluding domain discriminator

SER w/o EN : excluding encoding network



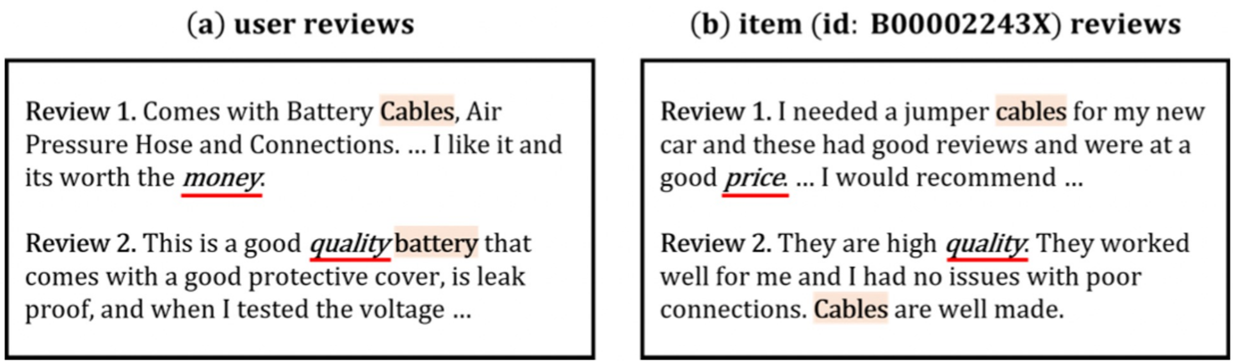
Experiment

Evaluation: nDCG@5(↑)



Italicized: domain-common

Colorized: domain-specific



Conclusion

- Domain discriminator can effectively remove noises from a source domain.
- Both common and specific knowledge are significant in cross-domain recommendation.